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Forecasting Electric Generation from Solar Energy Stephen D. Jascourt Daniel B. Kirk-Davidoff Christopher Cassidy Travis Hartman 820 W. Diamond Ave, Ste 300 Gaithersburg MD 20878 Stephen.Jascourt@mdaus.com MDA Information Systems, LLC

Overview

MDA Information Systems, LLC is predicting electric power generated from solar energy for individual sites and for regions. At last year's meeting, we presented about MDA's state-of-the-science *irradiance* forecasting system. This poster highlights challenges we have met for *predicting electric power generation*:

- Actual PV system performance differences from manufacturer specifications
- Malfunctions in site equipment
- Quality control of site data
- Snow on panels affecting PV generation
- Temporal variability affecting power-irradiance relationship and direct beam irradiance forecast

• Forecast uncertainty due to scenario differences

MDA Solar Power and Solar Irradiance Forecasting

MDA Information Systems, LLC has developed a solar forecasting system • Individual sites or collections of sites

- Distributed generation
- Panels of any tilt or sun-tracking
- All forecast lead times
- Prediction of
 - Solar power generation
 - Global Horizontal Irradiance (GHI)
 - Direct Normal Irradiance (DNI) and Direct Horizontal Irradiance (DIR) - Irradiance incident on panels
 - Working on sub-hourly variability prediction
 - MDA also predicts other parameters such as sunshine hours
 - Additional applications could include thermal load on buildings, etc.

MDA predictions of PV electric generation outperformed competition during our only head-to-head match-up so far

Our user interface shown here

- Is integrated into the wind power forecast display with the same features
- Allows viewing of forecasts for regions or individual farms
- Shows current and past forecasts and reported actuals to present
- Allows viewing of error statistics from recent forecasts
- In addition to the MDA power forecast, overlays model irradiance forecasts onto a map indicating power installation density, allowing the user to get a sense of the spatial and temporal distribution of incoming solar energy and its juxtaposition with electric generation capacity
- An improved user interface with more flexibility is coming soon! • Combined wind+solar power will be available for regions having large wind and solar capacity

Skill is dominated by prediction of clouds. Predicting evolution beyond

- the first few hours requires use of numerical weather prediction (NWP) models
- Cloud prediction is a weak point in NWP
- Time-averaged, not instantaneous, values of surface shortwave flux are needed
- Output frequency for most major NWP models is insufficient

• Surface shortwave fluxes from NWP models need complex bias correction (function of other variables) • Most NWP models do not output direct beam irradiance (DNI or DHI) and those that do provide it have little skill independent of predicted GHI

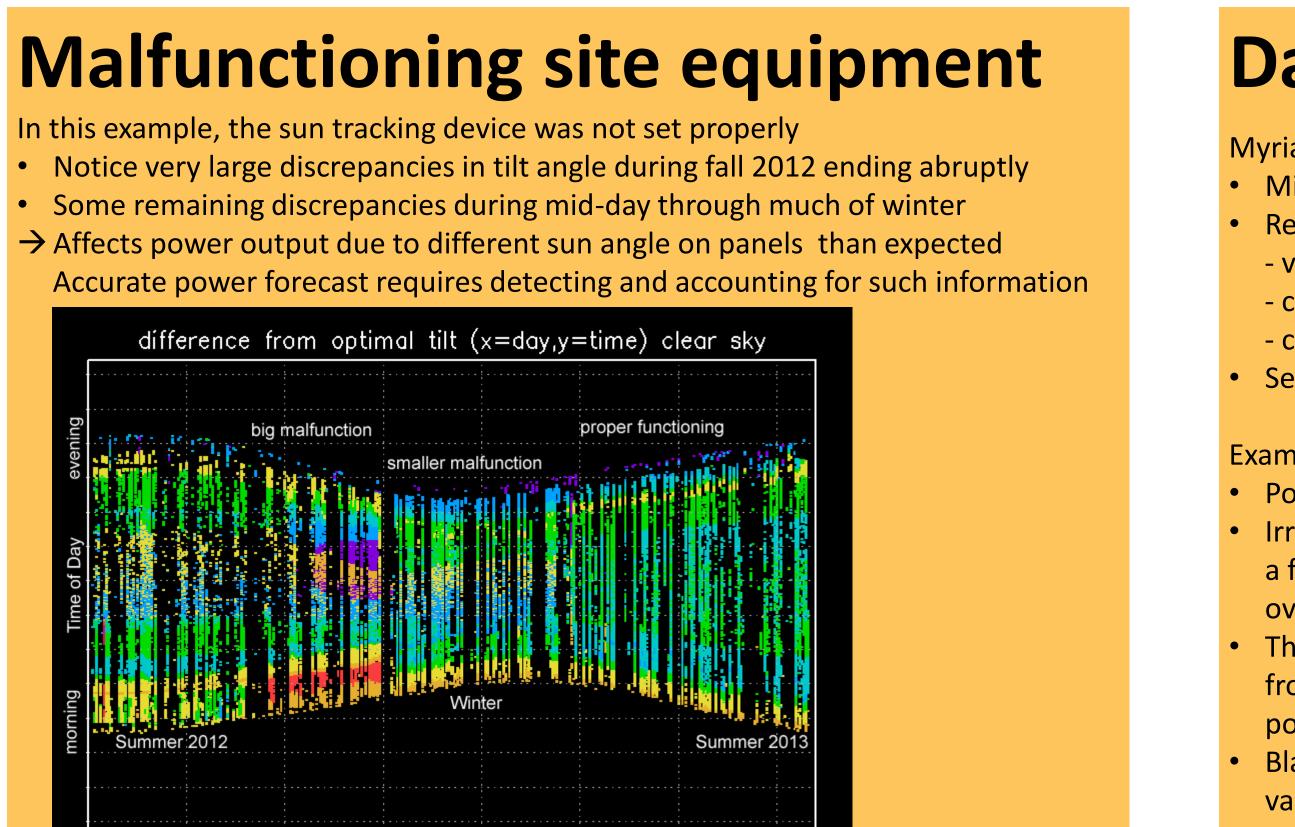
MDA Information Systems, LLC solar forecasting system meets these challenges through • Leveraging the REST2 (Gueymard, 2008) clear sky model as a foundation for time interpolation, bias correction, and direct beam calculation

- Employing a variety of public data sets to obtain aerosol-related and other parameters needed for REST2 and for considering cloudy atmospheres • NWP bias correction as a function of key variable combinations
- Skill-based blending of NWP models and time-lag ensembles

colors=angle (degrees)

-60 -40 -20 0 20 40 60 80

Reference: Gueymard, C. A., 2008: REST2: High-performance solar radiation model for cloudless-sky irradiance, illuminance, and photosynthetically active radiation – Validation with a benchmark dataset. Solar Energy, 82, 272-285



Reality vs. Manufacturer Specs

Electric generation ranged from 90% to over 120% of manufacturer specs based on site data (left) This example from eastern US location with abundant small cumulus clouds Power, plane-of-array irradiance, and GHI were measured on site

- Scatter possibly due to different operating conditions and perhaps from small cloud shadows moving across site
- Well-defined overall pattern as a function of total and direct-beam irradiance \rightarrow Empirical power relationship based on site data produces better power forecast than simple assumption applied to irradiance forecast

Panel tilt angle differed from specifications of tracking device (right)

- Ideally, panels would tilt more toward east in morning and west in evening (yellow) MDA calculations reveal that panels rest horizontal overnight, it takes around 2 hours to reach
- optimal tilt, peak panel tilt exceeds 45°, and peak tilt in evening exceeds peak tilt in morning
- \rightarrow Can use site data to detect actual conditions and utilize in prediction of power

MDA Renewables Monitor

Forecast

View the User Guide

Plot Granularity

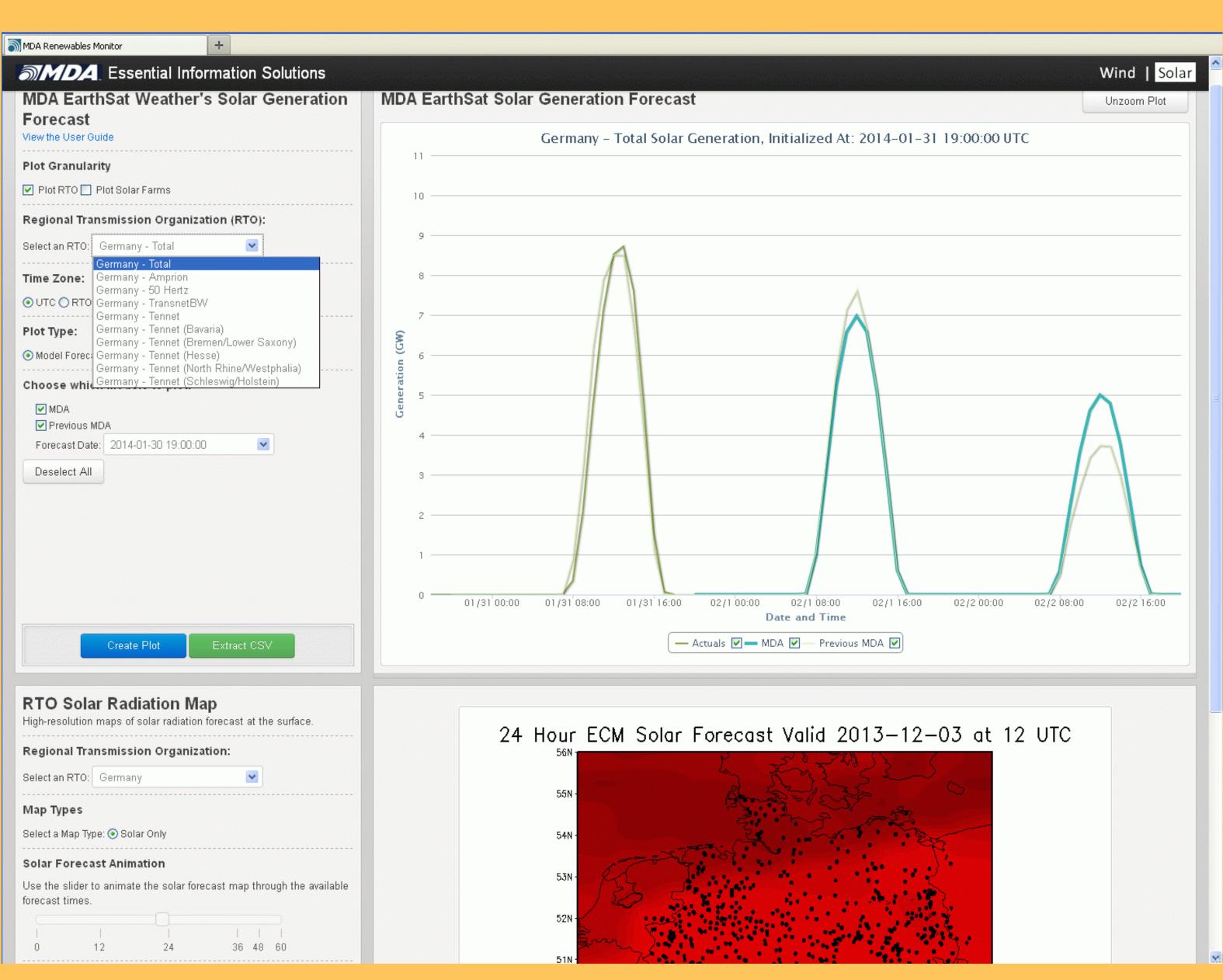
MDA

Map Types

forecast times.

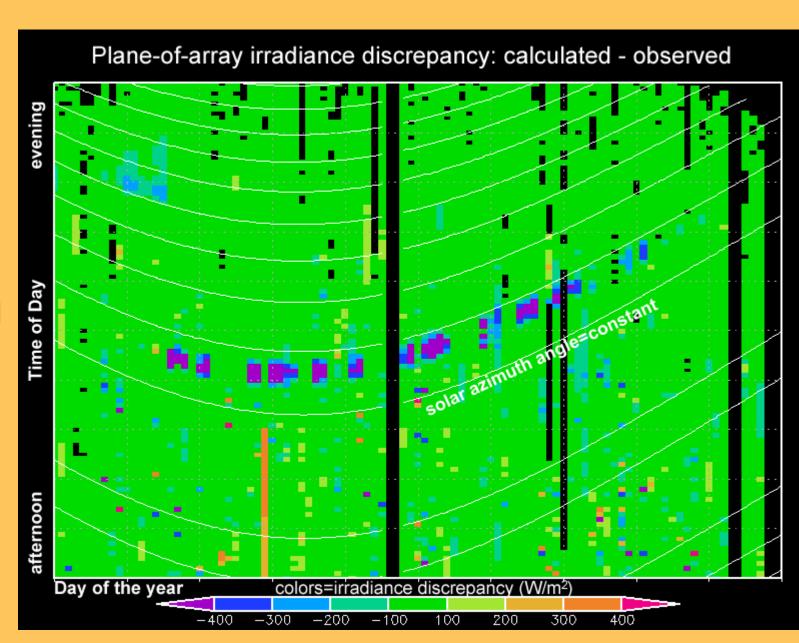
Previous MDA

Deselect All



Data Quality Control

- Myriad data quality control problems arise
- Missing data
- Recorder stuck
- value plausible stuck or actually steady? - compare several parameters simultaneously - check if power/irradiance ratios plausible Sensor artifacts and shadows
- Example shows shadow falling on sensor Power generation was not noticeably affected Irradiance reported was much too small for a few minutes at the same solar azimuth over several weeks on sunny days
- This data must be detected and removed from collection used to generate empirical power-irradiance relationships
- Black spots on plot indicate data filtered for various reasons; orange-yellow vertical stripe reveals other bad data not yet filtered



Device designed to tilt panels east up to 45° (-45) in morning, west up to 45° (+45) in evening (green)

Panel efficiency vs. 1-h averaged GHI 3-h averaged GHI 1-averaged DIR	
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200	
⁻¹⁰⁰ 92% 100% 120%	Î
% of manufacturer specs for Actual power	
Measured plane-of-array irradia	r

Temporal Variability

We found that the empirical power curve from site data varies with averaging time – for example, 1 hour vs. 2 minutes. This is related to sub-hourly variability in the direct beam irradiance due to changing cloud conditions (e.g., not due to changing sun angle under clear skies).

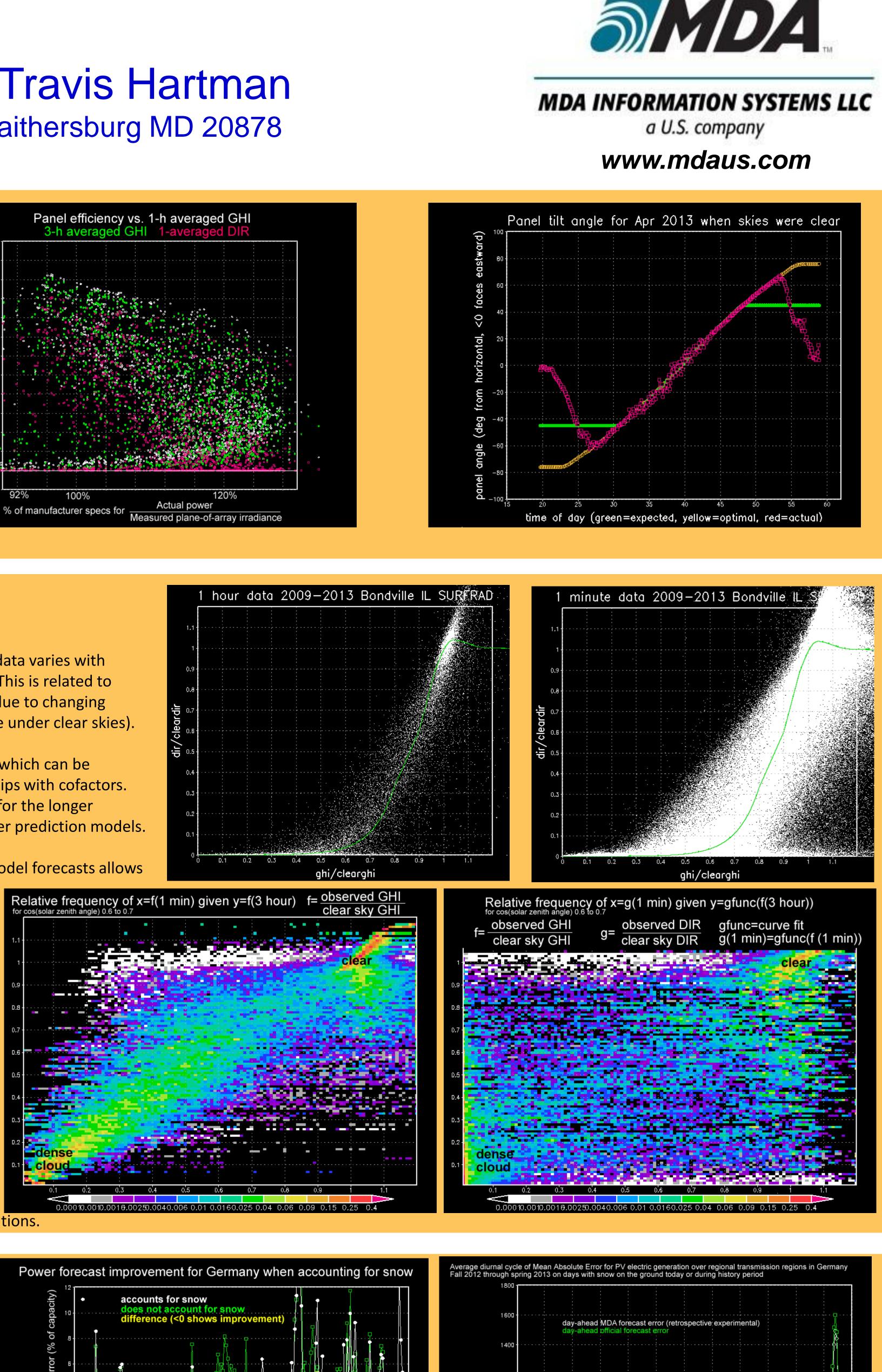
High temporal resolution data \rightarrow larger sample size which can be conditionally subsampled to refine power relationships with cofactors. However, these nonlinear relationships do not hold for the longer time-averaged data available from numerical weather prediction models

We found that adding stochastic perturbations to model forecasts allows using the more robust relationships from high temporal resolution data

 \rightarrow More accurate forecasts of hourly power \rightarrow Also yields forecast of subhourly variability!

Top: Fraction of clear sky GHI (x) vs. fraction of clear sky direct beam horizontal irradiance (y) for 4.5 years of data from the Bondville, IL SURFRAD site where points are from the 1-minute data (right) and for hourly averages (left) with the same curve shown in green. Clear sky values were calculated from REST2 Bottom: converts scatter from top plots into

relative frequency: given 3-hour fraction of clear sky GHI (left) or direct beam using the green curve (right), shows frequency of 1-minute values \rightarrow basis for stochastic perturbations.



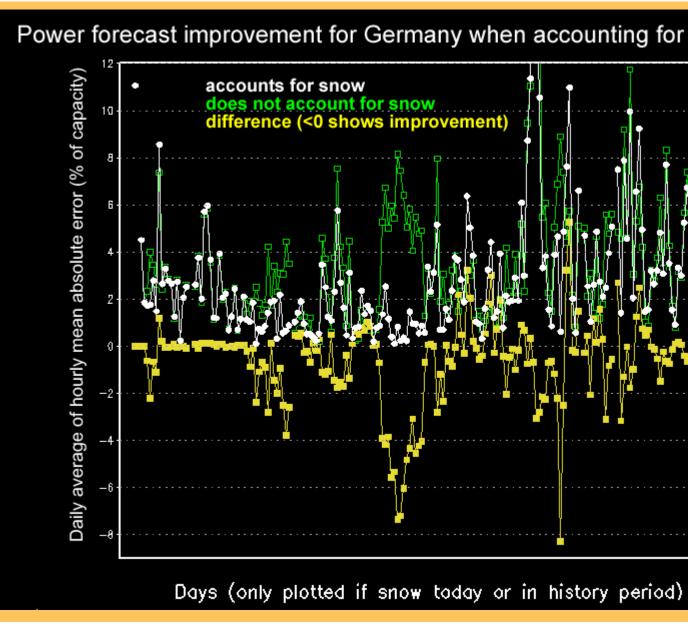
Snow

Snow on panels greatly diminishes power generation even on a sunny day. Power forecasts on subsequent days use these data for tuning.

Our algorithm tested for distributed generation across transmission regions in Germany

- Accounts for snow melting or sliding off panels
- before snow melts from ground Accounts sunlight transmitted through thin snow

Improvement in hourly generation forecasts: (left) resulting day-to-day improvement (right) seasonal average of diurnal cycle of MAE



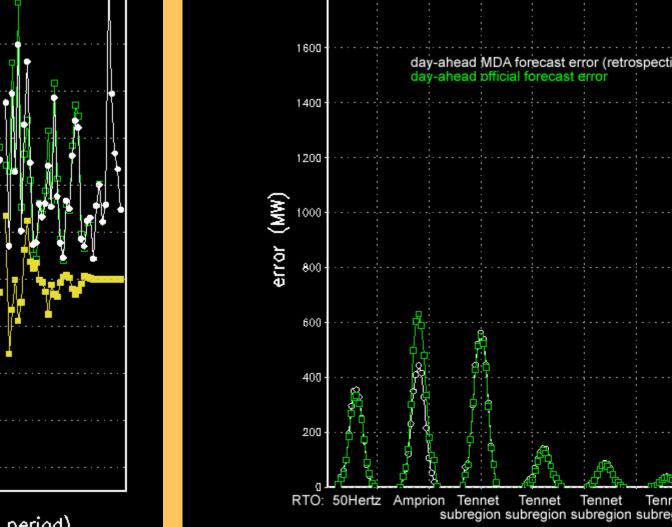
Uncertainty due to different forecast scenarios

The biggest challenge continues to be predicting the overall cloud scenario. To illustrate,

here are a series of days of hourly power forecasts from three commonly used numerical weather prediction models run through the MDA solar forecast system and plotted as a fraction of the power expected under clear skies for the same hour for this sun-tracking PV farm.

Models had largest errors and scatter at times when power generation was in the middle. All predicted a dreary day on day 7, but generation was even lower than predicted.

Ratio of h	ourly		da	y-ahea	d fore	casts	for 13	conse	cutive			
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day 1	2	3	4	5	6	7	8	9	10	11	12	13



ubregion subregion subregion subregion subregion

The Way Forward

Site data is crucial for developing good power-irradiance relationships • Plane-of-array irradiance together with electric power is most valuable - for sun-tracking systems, plane-of-array irradiance helps to

- determine actual orientations of the PV panels
- Quality control, high-quality data is crucial
- High temporal resolution is best this data can be time-averaged by the downstream user as desired
- Improved cloud forecasts is the tide that lifts all boats

• MDA is participating in the NCAR-led DOE-SunShot-funded solar forecasting project which is developing and testing the new state-of-thescience in cloud and irradiance prediction. MDA will be incorporating these new developments into the MDA solar power forecasting system

High-frequency variability may be key to predicting hourly power

- Nonlinear relationships differ over different averaging times • Sample size is larger using high-frequency data
- Variability such as from cumulus is different than scenario uncertainty
- We should think about how to better predict and distinctly express and use predictions of subhourly variability and scenario uncertainty